

## Research on Crowdsourcing Price Game Model in Crowd Sensing

Weijin Jiang<sup>1,2</sup>, Xiaoliang Liu<sup>1,2,\*</sup>, Dejia Shi<sup>1</sup>, Junpeng Chen<sup>1,2</sup>, Yongxia Sun<sup>1,2</sup> and Liang Guo<sup>3</sup>

<sup>1</sup>School of Computer Science and Technology, Hunan University of Technology and Business, Changsha, 410205, China

<sup>2</sup>Key Laboratory of Hunan Province for New Retail Virtual Reality Technology, Changsha, 410205, China

<sup>3</sup>School of Bioinformatics, University of Minnesota, Twin Cities, 15213, USA

\*Corresponding Author: Xiaoliang Liu. Email: vlzone@163.com

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**Abstract:** Crowd-Sensing is an innovative data acquisition method that combines the perception of mobile devices with the idea of crowdsourcing. It is a new application mode under the development of the Internet of Things. The perceptual data that mobile users can provide is limited. Multiple crowdsourcing parties will share this limited data, but the cost that the crowdsourcing party can pay is limited, and enough mobile users are needed to complete the perceptual task, making the group wisdom is really played. In this process, there is bound to be a game between the crowds and the mobile users. Most of the existing researches consider a group-aware system. A group of mobile users will directly share or compete for the opportunity of the crowd-holders to do tasks and get paid, the behavior of multiple crowd-source parties, and their bilateral interaction with mobile users. The research is not clear enough and there is no targeted research. This paper will model and analyze the dynamic evolution process of crowd sensing perception. Based on the unique characteristics of crowd-source non-cooperative game and crowd-sourced Nash equilibrium, we will develop a perceptual plan for mobile users and use the stability analysis of iterative algorithms to explore a way to better match the capabilities of mobile users and the needs of crowdsourced parties. Our theoretical analysis and simulation results verify the dynamic evolution model of crowdsourcing in group perception and propose a method to improve the efficiency of crowdsourcing.

**Keywords:** Crowd-sensing; crowdsourcing; incentives; sensor networks

### 1 Introduction

Crowd-Sensing is an innovative data acquisition method that combines the perception of mobile devices with the idea of crowdsourcing. It is an application under the development of the Internet of Things. It is an efficient way to create information in the world of Internet of Everything [1]. Crowd sensing refers to the formation of an interactive and perceptible network through widely distributed smart devices and mobile sensors. The individual users or group organizations in the network provide the data collector with the sensory information, and further



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process the acquired sensory information data deal with. Group-aware perception allows users to complete perceived tasks in an unconscious situation, breaking through the barriers of data collection. The Group is aware of flexible deployment, low cost, heterogeneous data sources, wide coverage and high expansion and multi-function [2].

Enterprises or organizations distribute their work through the Internet and accomplish tasks through the decentralized capabilities of massive network users. Crowdsourcing is a distributed problem solving method and production mode. The problem is communicated to the unknown user in an open manner [3]. The idea of crowdsourcing is to fully mobilize wisdom of the group and to complete complex tasks that are difficult to handle by traditional methods. A large number of mobile devices and IoT devices integrate rich sensors with powerful sensing, computing and communication capabilities, which makes the application of crowdsourcing ideas even more powerful. The Internet of Things will use the ubiquitous mobile devices to provide a larger, more complex, thorough and comprehensive sensing service that affects all aspects of social life, such as environmental monitoring, transportation, etc. [4]. At present, group-aware computing has attracted widespread attention and input from academics and smart vendors.

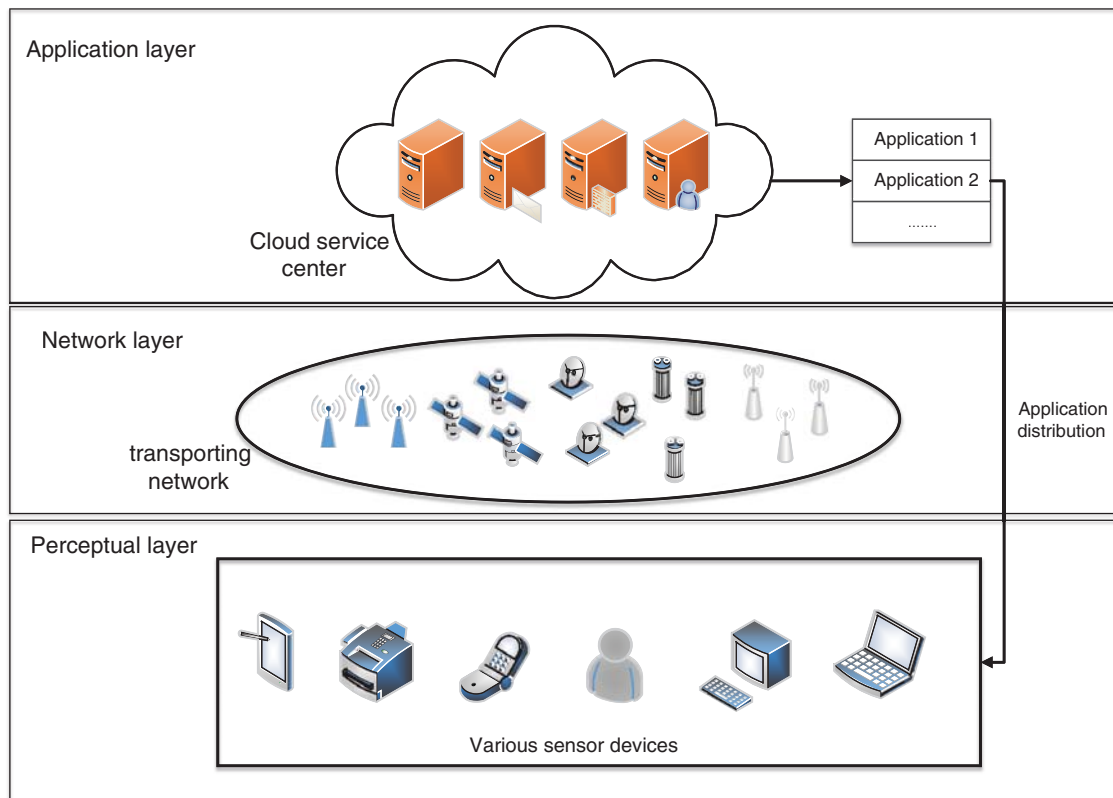
The prosperity of Crowd sensing computing will inevitably lead to the prosperity of the market-aware market. There will be multiple crowdsourcing parties in the market-aware market. Each crowd-buying party has different functions and different tasks. Users will get their own preferences. Selecting the crowdsourcing party. Since the perceived resources of the mobile users are not unlimited, the perceived data that the user can contribute is certain, and the data will be shared to multiple crowdsourcing parties. The crowdsourcing party will also be based on their own budget. Reasonably arrange the perceived resource demand, complete the task by summoning enough mobile users, and let the wisdom of the perceived resources be fully utilized. In the process of crowd sensing perception, there is a game between the crowdsourcing party and the mobile user, and the research is in the sense of crowd sensing. The relationship between multiple parties in the process, as well as the relationship between multi-package and mobile users, will better match the capabilities of mobile users and the needs of crowdsourcing parties. This paper will model and analyze the dynamic evolution behavior of multiple crowd-sources in group-aware networks [5].

## **2 Crowd Sensing System Architecture**

### **2.1 Crowd Sensing Network System**

The system architecture consists of three parts: the server platform, the data consumer and the data provider. It includes three layers: the perception layer, the network layer and the application layer. After the server accepts the service request from the data consumer, the perceived task is assigned to the mobile user. Through data backhaul, in this group-aware network system, the cloud server collects and processes the acquired data, and participates in other related activities for the processed result [6–9].

The crowdsourcing party sends the mobile user to the perceptual participant, and the perceptual participant reports the data to the server after completing the task, and the cloud service center completes the collection and processing of the perceptual data, and the cloud service center provides the data request after the data processing. By. Through the entire crowd sensing system to achieve data sensing, collection and service provision, crowd sensing is a large-scale integrated service with distributed computing properties, the process is shown in Fig. 1.



**Figure 1:** Systematic composition of crowd sensing

The basic workflow is described as follows:

The crowdsourcing party divides a perceptual task (for example, collecting air quality data) into several perceptual subtasks (for example, collecting air quality data for 5 min). Publish tasks and corresponding rewards to mobile users through open calls. Mobile users participating in group-aware tasks need to be paid to compensate for their resource consumption, such as people's time, energy, mobile device power, CPU and other resources.

After the mobile user knows the perceived task, it decides whether to participate in the perceived activity according to its own situation. In the case of multiple crowdsourcing parties in the market, decide which crowdsourcing parties and workloads to participate in. Mobile users participate in perceived activities, collect data, and use privacy protection to report data to the crowdsourcing party. The crowdsourcing party evaluates the perceived data and pays the mobile users.

The crowdsourcing party processes and analyzes all sensory data and builds various group-aware applications such as environmental monitoring, health monitoring, urban management, public safety, and intelligent transportation. The above process may take multiple rounds. Both crowdsourcing and mobile users are likely to adjust their behavior to meet target needs based on market reactions.

## 2.2 Crowd Sensing Perception Incentive Mechanism

Incentive mechanism design is an important issue in the group-aware network. The crowd-sourced party relies on the provision of a large number of mobile users to fully utilize the advantages of the group's wisdom. Mobile users also consume their own resources when participating in the perception, such as Set storage space, computing power, communication bandwidth, etc., and there may be a risk of privacy leakage. Therefore, the crowdsourcing party needs to provide compensation to mobile users to compensate for the loss of user resource consumption. The crowdsourcing party only designed one that can make the mobile Incentives for user satisfaction can attract enough users to participate in the provision of information, ensure the goal of data collection, and enable the perception function [10–12].

The main goal of the group-aware incentive mechanism is to allow more participants to participate in the provision of information. Under the incentives, the server platform can obtain more sensory data and actively participate in the perception task. The feedback quality is high. Trusted sensory data. The stimulus mode can be represented using the following pattern:

$$I: M = \max (U (S) , U (P)) \quad (1)$$

The model represents an incentive mechanism (incentive, referred to as I), that is, through a specific incentive (mechanism, referred to as M) to achieve the server platform (server, referred to as S) and participants (participants, referred to as P) utility (U) maximum.

## 2.3 The Problem of the Evolution of Crowd Sensing

The insufficient number of participants in the crowd sensing perception leads to insufficient sensory data. Participants want to get some compensation from the feedback process through feedback from the data, rather than voluntarily providing data free of charge. Because the perception and provision of data also consumes the cost of the participants, such as the lighting of smart devices, computing resources and data bandwidth costs, in the process of participation, individuals who provide data also need to consume a certain amount of energy. Without compensation, it is difficult for mobile users to maintain a certain level of enthusiasm in the provision of long-term perceived data.

The information that may be provided by the group's perceived participants may involve some private information. The information provided by the participants may include various types of information such as text, pictures, videos, etc. Most of the data is sensitive and private and may require a certain time and location. Due to the possible disclosure of privacy, participants may have some consideration for providing group-aware data and choose not to participate in the evolution of the group-aware process.

# 3 Analysis of Cooperative Behavior Among Multiple Public Parties

## 3.1 Problem Description and Modeling

Along with the continuous development of the group-aware network, the multi-functional group-aware applications are constantly emerging, which have a huge impact on all aspects of life. In the group-aware network, all crowd-buying parties purchase sensory services from the mobile user group. Mobile user resources are limited, and the perceived services that can be provided are limited. At this time, there is a competition among the crowdsourcing parties. The crowdsourcing party needs to adjust the compensation (that is, the price) paid to the mobile users, and the reasonable price can attract more. More users contribute data to help complete the perceived task.

Because there are multiple crowdsourcing parties in the market, the prices offered by different crowdsourcing parties are different, and the different quotes of multiple crowdsourcing parties will jointly affect the participants. The choice of crowdsourcing parties. The group-aware network with dynamic interaction between multiple crowdsourcing parties and mobile users needs further research in order to gain a deeper understanding of the group-aware network [13–16].

There are some challenges in studying dynamic evolution behavior of multi-packaged parties. First, mobile users will transform the crowdsourcing side of their services, and it is not easy to portray this. In addition, the claims of all participants in the group-aware market should be met. This includes selfish, all crowdsourcing parties that pursue the maximization of individual interests, and fully rational, mobile users who consider the most efficient when choosing crowdsourcing. There is currently no work to consider meeting the demands of both the task publisher and the mobile user. Only when the price competition of the crowdsourcing party ends in a steady state, all participants in the group-aware market will be satisfied. Second, market information is not completely revealed, which makes it more difficult to meet the first two constraints.

The group-aware market consists of multiple crowdsourced and participant groups.

We have a set of finite crowds in the group-aware market as  $M = \{1, 2, 3, \dots, m\}$ . note that  $M \geq 2$ , Assume that each crowdsourcing needs a group-aware awareness function, such as collecting vehicle traffic peak maps and marking images. Mobile users are free to choose among multiple task publishers to identify the crowdsourcing parties they want to provide perceived services. We give mobile users a strict meaning, that is, mobile device holders who provide cognitive services to crowdsourcing parties. We will not consider mobile device holders who enjoy group-intelligence-integrated group-aware capabilities. We view the mobile user community as a continuum of the same type of service provider, also known as a representative service provider.

Interaction process is as follows:

The crowdsourcing party issues tasks to the participants, who complete the tasks and receive the rewards provided by the crowdsourcing parties. The perceived participant can get the reward  $p_i$  for the task of the crowdsourcing party  $i$  to do the unit time.

Participants are free to choose whether to participate in the provision of sensory data and how much data is provided to these task publishers. This process is called the provision of sensory data. We use the number of units of time to assess the number of perceived services that a crowdsourcing party attracts. For example, mobile users are willing to contribute  $a_i$  unit time of perceptual data to the crowdsourcing party  $i$ . Mobile users will join the crowdsourcing party that makes them happy.

Description of parameter  $a_i$ : We assume that a single mobile user can only serve one crowd of people at a time. If a time dimension is added to the group-aware market, assuming that a single mobile user contributes only data per unit time per time slot, then  $a_i$  is also the number of mobile users joining the crowd-crowding party  $i$  in the time slot.

Each task publisher party pursues at the lowest cost and will strategically adjust the price to achieve the desired benefits.

Here we define the perceived contribution of the mobile user to the crowdsourced party as “service supply.” In this paper, we use “service supply substitutability” to express the willingness of mobile users to transform their services. this is inspired by the concept of “substitute good” in economics. “Substitute good” has a positive cross elasticity of demand, which means that the demand for goods A will rise as the price of goods B rises. In the group-aware market, unlike

goods or services being sold, crowdsourcing parties purchase perceived services. The willingness of mobile users to join crowdsourcing party A will increase as the price offered by crowdsourcing party B rises [17].

Mobile users respond to all crowdsourcing party pricing strategies and develop a perceptual plan that maximizes revenue. The perception plan in turn affects the price adjustments of the crowdsourcing party. We focus on the market segmentation of service offerings and the price adjustment process of crowdsourcing parties.

Mobile user utility is affected by the rewards of providing perceived services and the cost of doing perceived tasks. The utility of mobile users does not always increase. if a perceived task can get higher rewards, usually this perception also consumes more cost. Therefore, the utility of mobile users will be met after reaching a certain level.

The utility function of the mobile user is as follows:

$$\pi(a) = \sum_{i=1}^M a_i p_i - \frac{1}{2} \left( \sum_{i=1}^M a_i^2 + 2v \sum_{i \neq j} a_i a_j \right) - \sum_{i=1}^M a_i c_i \quad (2)$$

where  $a_i$  indicates that the representative mobile user is willing to contribute  $a_i$  unit time of perceptual data to the crowdsourcing party  $i$ .  $a = \{a_1, \dots, a_n, \dots, a_M\}$  represents a collection of service offerings for all crowdsourced parties.  $p_i$  is the price per unit time-aware data that the crowdsourcing party  $i$  pays to the mobile user.  $c_i$  is the cost of the mobile user contributing unit time-aware data to the crowdsourcing party  $i$ .  $v \in [0.0, 1.0]$  means “service supply substitutability.” when  $v = 0.0$ , mobile users are reluctant to change the crowdsourcing side of their service;  $v = 1.0$ , mobile users change the crowdsourcing side of their service very frequently. Each crowdsourcing party self-adjusts the price to get the most profit. The profit of the crowdsourcing party is derived from the profit minus the cost. The profit of the crowdsourced party is obtained from the perceived service provided by the mobile user, and the cost is paid to the mobile user. The profit function of crowdsourcing party  $i$  is:

$$P_i(p) = R_i(a_i) - C_i(a_i) \quad (3)$$

Among them,  $R_i(a_i) = \sigma a_i$ ,  $C_i(a_i) = p_i a_i$ ,  $\sigma > 1$  is the system parameter,  $0 < p_i < \sigma$ .  $a_i$  reflects the profit of the crowdsourcing party  $i$ .

The impact of mobile user feedback on crowdsourcing revenue can be divided into three modes: the benefits of crowdsourcing parties without information feedback strategy; the benefits of crowdsourcing parties under full information feedback strategy; and the benefits of crowdsourcing parties under partial information feedback strategies [9–11].

If the crowdsourcing party chooses not to feedback the participants’ scores, each participant knows only his or her effort in the first stage, and the effort levels of the other participants are private information. The equilibrium effort levels of Contestant A and Contestant B are the same in both phases. That is, the no-information feedback strategy contest is equivalent to a single-stage, single-prize contest. Participant A chooses to maximize effort in the first and second stages to maximize its utility, and similarly, Participant B does the same. In a crowdsourcing competition, if the crowdsourcing party adopts a full information feedback strategy, the participant can know the output of the other participants from the scores fed by the crowdsourcing party and derive the difference between the output of the other participants in the first stage and his own and use backward extrapolation to determine the level of effort in the second stage. Full information



feedback is the same as the first stage under partial information feedback, with the difference that under the full information feedback strategy, the crowdsourcing party reveals to the participants that their score difference is a specific value at the end of the first stage of the competition. When the crowdsourcing party adopts a partial feedback strategy, it discloses their first stage score difference to the participants. The score difference function allows participants to predict their competitors' effort levels and thus determine their effort levels. [12–14].

### 3.2 The Mobile User Specifies the Awareness Plan

For all the policy sets of crowdsourcing parties, mobile users will make a perception plan, that is, how much data they contribute to each crowdsourcing party respectively, so as to obtain the highest utility.

We can get the perception plan from the utility function of mobile users in equation Eq. (2).

I'm going to take  $\pi(a)$  with respect to  $a$ , and I'm going to set it to 0, this means how to set the value of  $a$  to maximize the utility  $\pi(a)$ .

$$\frac{\partial \pi(a)}{\partial a_i} = 0 = p_i - a_i - v \sum_{i \neq j} a_j - c_i \quad (4)$$

Through simultaneous  $M$  equations Eq. (7), We can get every element of  $a = \{a_1, \dots, a_i, \dots, a_M\}$ , which is the perception plan of mobile users. Here we use  $W_i(p)$  instead of  $a$ , as shown below

$$W_i(p) = \frac{(p_i - c_i)[1 + v(M - 2)] - v \sum_{i \neq j} (p_j - c_j)}{(1 - v)[1 + v(M - 1)]} \quad (5)$$

For the sake of simplicity, we rewrite the mobile user's perception plan equation Eq. (6) as follows:

$$W_i(p) = D_2 p_i - D_1 (p_{-i}) \quad (6)$$

among them,  $D_1 (p_{-i})$  and  $D_2$  is a constant, Given all  $p_j$  ( $i \neq j$ ) cases. Their expressions are as follows:

$$D_2 = \frac{1 + v(M - 2)}{(1 - v)[1 + v(M - 1)]} \quad (7)$$

$$D_1 (p_{-i}) = \frac{c_i [1 + v(M - 2)] + v \sum_{i \neq j} (p_j - c_j)}{(1 - v)[1 + v(M - 1)]} \quad (8)$$

Note that the perception plan of mobile users is actually the service supply share of the crowdsourcing party.

### 3.3 Uniqueness of Nash Equilibrium for Crowdsourcing Party

We will prove that the optimal response of each crowdsourced party is unique. Therefore, the Nash equilibrium of the crowdsourcing price game is also unique.

The optimal response  $BR(p_{-i})$  of the crowdsourcing party is unique.

**Prove.** Given service supply  $W_i(p)$ , The profit of crowdsourcing party i is:

$$P_i(p) = (\sigma - p_i) W_i(p) \quad (9)$$

In order to find the optimal response of the crowdsourcing party i, we calculate the derivative of  $P_i$  to  $p_i$ :

$$\frac{\partial P_i(p)}{\partial p_i} = -2D_2 p_i + D_1(p_{-i}) + \sigma D_2 \quad (10)$$

$$\frac{\partial^2 P_i(p)}{\partial p_i^2} = -2D_2 \quad (11)$$

Because the second derivative of  $P_i$  to  $p_i$  is non-negative, the profit function  $P_i$  of the crowdsourcing party i is strictly concave function on  $p_i$ . Therefore, given the strategy set of any other crowdsourcing party, crowdsourcing optimal reaction strategy for square  $BR_i(p_{-i})$  is unique.

Next, calculate the optimal response strategy of crowdsourcing party i. Set  $P_i$  to  $p_i$ ; the first derivative is 0, we have:

$$-2D_2 p_i + D_1(p_{-i}) + \sigma D_2 = 0 \quad (12)$$

so let's solve for  $p_i$ :

$$p_i = \frac{D_1(p_{-i}) + \sigma D_2}{2D_2} \quad (13)$$

Simultaneous Eqs. (7), (8) and (13):

$$p_i = \frac{1}{2} \left[ \frac{\sum_{j \neq i} (p_j - c_j)}{v(M-2) + 1} v + c_i + \sigma \right] \quad (14)$$

### 3.4 Analysis of Experimental Results

We have simulated a group-aware market with two crowdsourcing parties through a series of experiments. We call the two crowdsourcing parties A and B. We pay attention to the following points: First, service supply alternatives to Nash equilibrium The second is the impact of Nash equilibrium convergence on price dynamics; the third is the stable region of the learning rate that makes the price adjustment iterative algorithm converge when a crowdsourcing party cannot observe other crowdsourcing strategies.

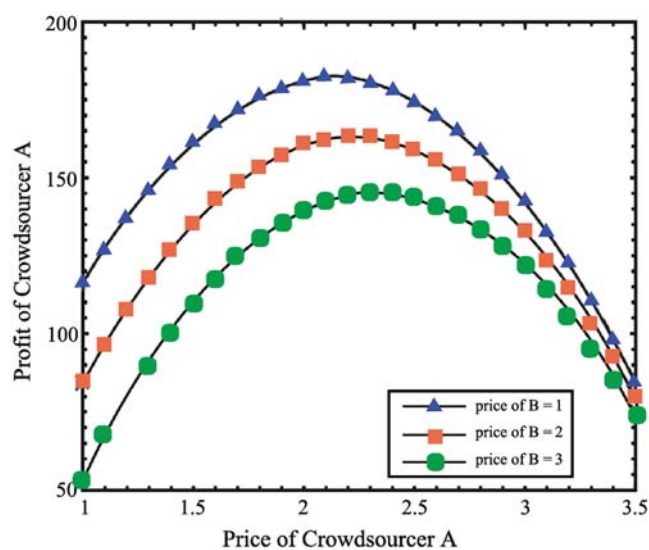
The experimental environment is Matlab R2018a running on a Windows 10 system. The default settings are as follows: System parameter  $\sigma = 4$ . The cost of a mobile user doing tasks for crowdsourcing parties A and B respectively is  $c_1 = 0.1$  yuan and  $c_2 = 0.5$  yuan. Service supply alternative change between 0.2 and 0.8. The setting of these parameters gives mobile users a reasonable return. The setting of these parameters also has a certain relationship with the simulation environment.

#### 3.4.1 The Optimal Response of the Crowdsourcing Party

The profit of the crowdsourcing party A is expressed as a function of its price, As shown in Fig. 2. Before a certain point, the profit of the crowdsourcing party A increases as the price increases. Because the higher the price means the crowdsourcing party pays the higher the reward



for mobile users, the more mobile users can contribute to perceived services. After this particular point, the profit of crowdsourcing party A decreases as the price increases. Because the increase in profits cannot compensate for the increase in prices. The optimal response is the price at which the crowdsourcing party obtains the highest profit. The optimal response of the crowdsourcing party A increases with the price increase of the crowdsourcing party B, which is a good explanation for the positive cross elasticity of demand.



**Figure 2:** Optimal response of crowdsourcing party A

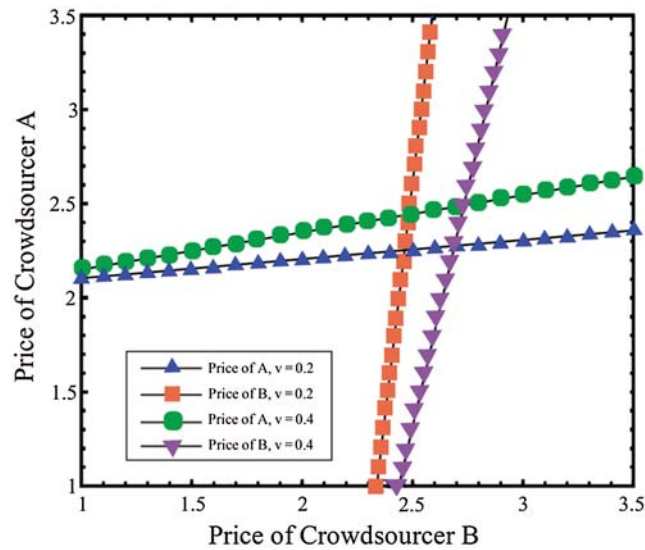
### 3.4.2 Nash Equilibrium of Static Non-Cooperative Game in Crowdsourcing Party

As shown in Fig. 3, the optimal response function of crowdsourcing parties A and B crosses at a certain point, which means that at this point, both the crowdsourcing parties A and B choose the optimal response strategy, which is the Nash equilibrium point. The Nash equilibrium price  $p_2$  of the crowdsourcing party B is higher than the Nash equilibrium price  $p_1$  of the crowdsourcing party Alice, because the cost of the mobile user contributing data to the crowdsourcing party B is also higher than the cost of contributing data to the crowdsourcing party A. When the service supply substitutability  $v$  is higher, the price of the Nash equilibrium is also higher. Because mobile users change the crowdsourcing of their services at a higher frequency (usually to the more highly paid crowdsourcing party), each crowder needs to increase the price to attract more mobile users.

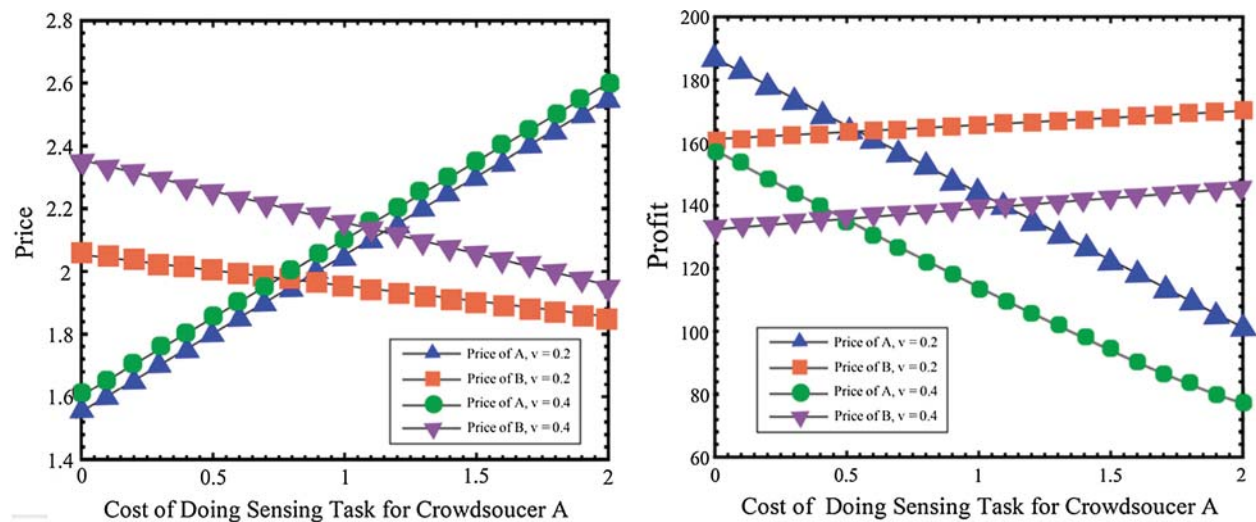
### 3.4.3 The Impact of Mobile User Spending on the Price and Profit of Crowdsourcing Parties Under Nash Equilibrium

Fig. 4 respectively show the changes in the price and profit of the crowdsourced party under the Nash equilibrium with the cost of the mobile user (the cost of doing the task for the crowdsourcing party A). We found that the service supply substitutability  $v$  has a higher impact on crowdsourcing parties A and B: the price of crowdsourcing party A is only slightly affected, and the price of crowdsourcing party B is decreasing at a higher rate. We explain this phenomenon in this way: when the cost of the mobile user serving the crowdsourcing party B remains unchanged, and the cost of serving the crowdsourcing party A increases, the mobile user gets more benefits from the crowdsourcing party B than the crowdsourcing party. A gains are high. When the service

supply alternative  $v$  becomes larger, the mobile user shifts to the crowdsourcing party B to provide a perceived service at a higher frequency, so that the share of the service supply obtained by the crowdsourcing party B increases.



**Figure 3:** Nash equilibrium of static non-cooperative game in crowdsourcing



**Figure 4:** Changes in the price and profit of crowdsourcing party under Nash equilibrium with the cost of mobile users

Therefore, the crowdsourcing party can lower the price at a faster rate while ensuring an increase in profits.

### 3.4.4 A Stable Region of the Learning Rate that Causes the Price Adjustment Iterative Algorithm to Converge

When the crowdsourcing party cannot observe the strategy of other crowdsourcing parties, the learning rate is crucial for the convergence of the iterative algorithm. In this section, we will explore the stable region of the learning rate that converges the price-adjusted iterative algorithm. The experimental results are shown in the Fig. 5. When the learning rates  $Q_1$  and  $a_2$  are taken from the stable region, the crowdsourcing iterative algorithm can successfully converge to the Nash equilibrium. We have found that there is disturbance when the service supply becomes more substitutable.

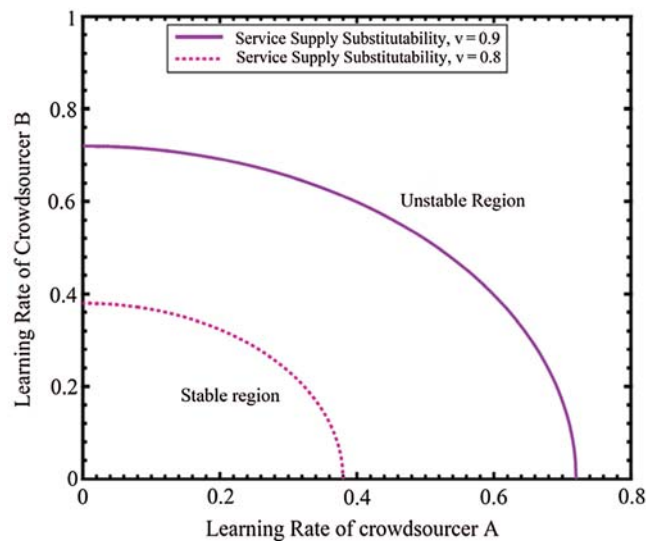


Figure 5: Stable area of learning rate

## 4 Multi-Party Party Competition Behavior Analysis

### 4.1 Proposal and Analysis of the Problem

Due to the amount of perceived resources provided by participants, there will be competing behavior among multi-party parties. The study found that Nash equilibrium stability does not allow the crowdsourcing party to obtain the largest overall profit. When the crowdsourcing parties cooperate, the optimal overall profit will be obtained. However, the partnership between the crowdsourcing parties is not stable because the partnership is not based on the best response function, which means that there are viable strategies to increase the profitability of one or more crowdsourcing parties [18–20]. This is especially true when the game is only played once, because the crowdsourcing party does not have long-term profits to consider. If the game is conducted multiple times, the crowdsourcing party may consider cooperative behavior when considering long-term profits. The group-aware network is in a dynamic change, and there will inevitably be multiple interactions between the crowdsourcing parties. Therefore, in the perfect research system of the dynamic evolution mechanism of group-aware network, the cooperative between multiple parties needs to be studied. It is also necessary to analyze the conditions formed by the cooperation between the crowdsourcing parties. We conduct research on a multi-packaged group perception model in the market [21–23].

#### 4.2 The Best Price of the Crowdsourcing Party

The crowdsourcing party wants to get the best price for the highest profit. The optimal price is different from the price at which the Nash equilibrium is reached. Therefore, the crowdsourcing parties may cooperate to obtain the highest profit.

The optimal price of the crowdsourcing party will be obtained by the following equation:

$$\frac{\partial \sum_{i=1}^M P_i(p)}{\partial p_i} = 0 \quad (15)$$

Among them,  $\sum_{i=1}^M P_i(p)$  is the sum of the profits of all the crowdsourcing parties.

For the special case with only two crowdsourcing parties (i.e.,  $M = 2$ ,  $i = 1$ ,  $j = 2$ ), the optimal price is as follows:

$$p_i = \frac{1}{3} [(2p_j - c_j) v + c_i + (1 - v) \sigma] \quad (16)$$

$$p_j = \frac{1}{3} [(2p_i - c_i) v + c_j + (1 - v) \sigma] \quad (17)$$

For a special case with only two crowdsourcing parties (i.e.,  $M = 2$ ,  $i = 1$ ,  $j = 2$ ), the price to reach the Nash equilibrium is as follows:

$$p_i = \frac{1}{2} [(p_j - c_j) v + c_i + \sigma] \quad (18)$$

$$p_j = \frac{1}{2} [(p_i - c_i) v + c_j + \sigma] \quad (19)$$

It is obvious that the optimal price is different from the price of reaching the Nash equilibrium. This special case can be extended to the case where  $m > 2$  has any number of crowdsourcing parties.

#### 4.3 Cooperative Strategy Conditions

A long-term cooperation between a crowdsourcing party and other crowdsourcing parties depends on the long-term benefits. If she can get a higher long-term profit from cooperation than non-cooperation, it will agree to maintain cooperation with other crowdsourcing parties. The crowdsourcing party deviates from the optimal price, that is, she hopes to increase her profit by attracting more perceived services by raising the price. However, other crowdsourcing parties will adopt Nash, which has a higher price than her. Equilibrium prices, the market will punish its behavior. Therefore, the deviation of the crowdsourcing party will get the profit under the deviation strategy in the first stage and get the profit under the Nash equilibrium strategy in the remaining stage. We use an example to explain the crowdsourcing the square repeats the game model. Suppose there are two crowdsourcing parties called A and B. In the first phase, they choose to cooperate with each other. In the second phase, the crowdsourcing party chooses to deviate from the strategy and raise the price to obtain more profit. And the crowdsourcing party B does not know the choice of the current stage when deciding the strategy, continuing to choose cooperation, maintaining the best price. In the third stage, the crowdsourcing party B knows the deviation behavior of a in the previous stage, will punish A, raise the price higher to Nash equilibrium price. In order to deal with this situation, the best choice for the crowdsourcing

party is to set the price as the Nash equilibrium price. Here, the cooperation breaks down, and the crowdsourcing parties a and b cannot benefit from it. In the next stage the situation is the same as the third stage.

The best price is that the crowdsourcing parties cooperate with each other and use this price to get the highest overall profit. The optimal response price, that is, crowdsourcing and mutual competition, can be used to achieve Nash equilibrium [24–26].

The meanings of related symbols are shown in Tab. 1.

**Table 1:** Meanings represented by symbols

Character	Meaning
$P_i$	The current stage of the crowdsourcing party i profit
$\gamma P_i$	The next stage of the crowdsourcing party i profit
$P_i^o$	The crowdsourcing party chooses the profit of cooperation at a certain stage.
$P_i^d$	The crowdsourcing party i chooses the profit of betrayal cooperation at a certain stage.
$P_i^n$	The crowdsourcing party i chooses the profit of the Nash equilibrium strategy at a certain stage.

We use  $\gamma_i$  to indicate the discount factor, which means that the profit of the current stage of the crowdsourcing party is more valuable than the profit of the future stage. To the crowdsourcing party i,  $P_i^o$ ,  $P_i^d$ ,  $P_i^n$  is said that it chooses the cooperation, the deviation from cooperation, and the profit of the punishment strategy. The following is a calculation of the long-term profit of the crowdsourcing party i using different strategies.

The crowdsourcing side uses the long-term profit of the cooperative strategy at each stage:

$$P_i^o + \gamma_i P_i^o + \gamma_i^2 P_i^o + \gamma_i^3 P_i^o + \dots = \frac{1}{1 - \gamma_i} P_i^o \quad (20)$$

The crowdsourcing party uses the long-term profit of the deviation strategy:

$$P_i^d + \gamma_i P_i^n + \gamma_i^2 P_i^n + \gamma_i^3 P_i^n + \dots = P_i^d + \frac{\gamma_i}{1 - \gamma_i} P_i^n \quad (21)$$

Then the condition that the crowdsourcing party chooses the cooperation strategy is that the long-term profit of the selection cooperation strategy is higher than the long-term profit of the selection deviation strategy, that is:

$$\frac{1}{1 - \gamma_i} P_i^o \geq P_i^d + \frac{\gamma_i}{1 - \gamma_i} P_i^n \quad (22)$$

From this we get the discount factor  $\gamma_i$  lower bound:

$$\gamma_i \geq \frac{P_i^d - P_i^o}{P_i^d - P_i^n} \quad (23)$$

Discount factor  $\gamma_1$  when the value is higher than the lower bound, the crowdsourcing parties will cooperate. They use the best price at each stage to get the highest profit, which in turn gives them the highest long-term profit.

We study the cooperation behavior among multi crowdsourcing party. The crowdsourcing party will not get the optimal global profit by adopting the price strategy of Nash equilibrium. When the interaction between crowdsourcing party is repeated, crowdsourcing party may cooperate considering long-term profits. But the cooperation relationship is unstable, because there are always crowdsourcing party who can get higher profits by deviating from the cooperation. We model the cooperative behavior of multi crowdsourcing party as a repeated game and analyze the conditions of the cooperative behavior of multi crowdsourcing party.

We experimented with the simulation of the market-aware market with two crowdsourcing parties to support the previous theoretical analysis. We call the two crowdsourcing parties A and B respectively. The simulation setup of the experiment is the same as the cooperative behavior experiment. The experimental results are shown in Fig. 6. We have found that crowdsourcing parties can indeed benefit from cooperative behavior. A crowd-carrying party maintains cooperation by choosing the best price, which is lower than the best response price. All crowdsourced parties will adopt the optimal response price and gradually reach a Nash equilibrium. A higher optimal response price means that the crowdsourcing party will pay more for mobile users. The cost of competition among crowdsourcing parties will also increase. The deviation price is higher than the optimal price and lower than the optimal reaction price.

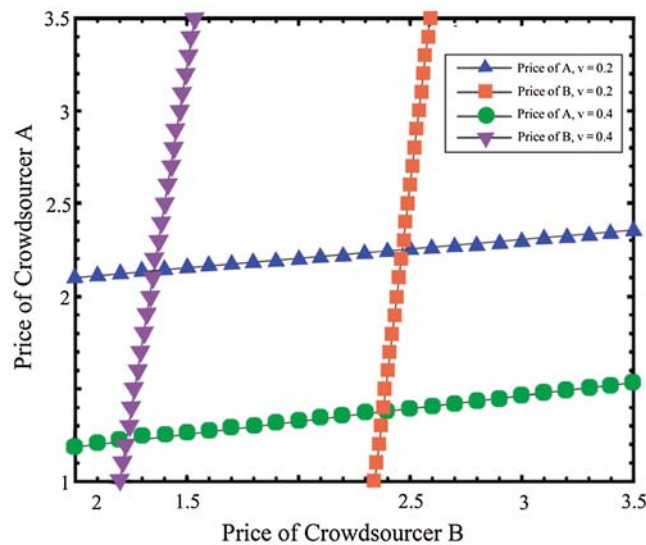


Figure 6: Optimal price and optimal response price

## 5 Conclusion

This paper conducts an in-depth study of the multi-crowd competition and cooperation behaviors in the group-aware network and explores the research mechanism of the dynamic evolution mechanism of the group-aware network. With the continuous application of group-awareness, users are not only limited in providing perceived services. For specific crowdsourcing parties,



and with more reference, they are free to choose private rooms. Crowders need to be attracted to specific users, collect enough data from users, and exert collective capabilities. Maximize the benefits of the crowdsourcing party. Multi-bundle parties will compete for the perceived services provided by mobile users. We model the price competition between multiple crowdsourcing parties into a dynamic non-cooperative game for crowdsourcing. The distributed learning algorithm is designed to converge to Nash equilibrium. Thus, the price of eating crowd sensing is balanced after a certain period of change, rather than endless price adjustment.

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**Conflicts of Interest:** The authors declare that they have no conflicts of interest to report regarding the present study.

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